A demand-driven analysis of tourist accommodation price: a quantile regression of room bookings

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Abstract

Tourist accommodation price is a widely investigated topic as it represents a major contribution to the total tourist expenditure. The identification of the determinant factors is commonly based on supply-driven applications and, while little research has been made on important travel characteristics. This paper presents a demand-driven analysis of tourist accommodation price by focusing on data generated from room bookings. The investigation focuses on modeling the relationship between major travel characteristics and the price paid to book the accommodation. To accommodate the distributional characteristics of the expenditure variable, the analysis is based on the estimation of a quantile regression model. The findings support the econometric approach used and enable the elaboration of relevant managerial implications.

Keywords: *hotel booking; accommodation expenditure; quantile regression*

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1. Introduction

Tourist expenditure represents an important topic in the tourism research agenda, and several studies on this topic have analyzed the determinant factors (see Brida and Scudieri, 2013 for a comprehensive review). The general interest of most studies is to develop a better understanding of the total tourist expenditure, which by definition includes the spending for all the different products that comprise the travel experience. In this context, accommodation is a major component of tourist expenditure (Laesser and Crouch, 2006), and the investigation therefore facilitates both direct implications for the hospitality industry and indirect implications for the tourism industry as a whole.

Generally speaking, the economic analysis of tourism accommodation is based either on supply (room prices) or demand (tourist expenditure) data. In particular, accommodation pricing is mainly investigated from a supply perspective through the estimation of hedonic regression. In this approach, the publicized room prices are regressed on a set of hotel and hotel room attributes that are assumed to determine the price of the room (Espinet, Saez, Coenders, and Fluvià, 2003). On the other hand, the analysis of demand data typically allows the investigation of the factors influencing tourist revealed expenditure, including economic constraints, socio-demographic, trip-related and psychographic factors (Brida and Scudieri, 2013).

The condition of market equilibrium is barely supported in the hospitality industry (Chen and Chiu, 2014), and the use of supply-driven data for the analysis of accommodation price comes with a limitation as the room price levels do not necessarily reflect the actual tourist expenditure for accommodation. In this regard, demand-driven data, in the form of actual accommodation bookings, can provide an original source of information for the analysis of price dynamics by focusing exclusively on tourists' effective expenditure. The current study proposes the analysis of accommodation price based on data generated from actual demand behavior. The investigation focuses on major travel characteristics (such as length of stay, travel party size, advance booking, selected sales channel, season, and purpose of travel) and their relationship with the price paid is modeled through regression techniques.

The distribution of the tourist expenditure is generally characterized by a long tail (Huana, Beaman, Changd, and Hsu, 2008) because of the concentration of large values on the right tail of the distribution. Hence, the traditional Ordinary Least Square (OLS) regression methods, which are commonly used in the tourist expenditure literature, present the risk of undesirable estimate results. Quantile regression has therefore been used increasingly in the past decade in a variety of contexts, and is especially suitable for the analysis of asymmetric variables and long-tail distributions because the method reduces the weight placed on extreme observations (Koenker and Basset, 1978). Quantile regression further increases the interpretability of the results as separate coefficients are estimated for different quantiles of the dependent variables. Nevertheless, the application of quantile regression in the tourism context is quite recent (Brida and Scudieri, 2013), and is limited to only few instances. The following application applies the quantile regression technique in an attempt to consolidate the use of the appropriate estimation method for the investigation of tourist expenditure.

Therefore, this paper contributes to the current literature by proposing a quantile regression model for the investigation of tourist accommodation price from a demand-driven perspective. In particular, the spending of tourists for accommodation at the destination refers to actual bookings registered from different online and offline booking sources through a channel manager. By comparing the estimates from OLS and quantile regressions, this paper provides additional evidence on the use of quantile regression for an expenditure model and investigates key travel characteristics and variables of interest.

To the best of the authors' knowledge, the proposed analysis represents the first demand-driven application that estimates a quantile regression model on tourist accommodation bookings. The findings enhance the understanding of the role played by the variables included in the analysis. In particular, the estimation of a quantile regression allowed the identification of a differentiated effect in the conditional distribution of accommodation expenditure for variables such as star classification, distribution channel and travel party size. Meanwhile, the investigation of transactions effectively made on the market allowed the investigation of travel characteristic aspects from a demand perspective.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and outlines the Methodology. Section 4 presents the results, and Section 5 concludes the paper by discussing the theoretical and managerial implications of the study and directions for future research.

2. Literature Review

Hospitality and tourism researchers have largely examined the effects of hotel room rates and the determining factors. Generally, previous studies in the area fall into two major categories, namely, the analysis of the factors that influence hotel room rates, and that of the pricing strategies of the hotel management.

2.1 Room Rate Determining Factors

Considering that lodging is an industry that is appropriate for hedonic analysis, Zhang, Zhang, Lu, Cheng, and Zhang (2011) examined how site and situation attributes can affect room prices and the lodging industry in Beijing. The fitting coefficient of geographically weighted regression demonstrates the importance of the global modeling framework. Specifically, star rating, hotel age, and location can influence hotel room prices, whereas room number and distance from the hotel to transportation hubs have negatively significant effects on room prices. The findings, according to the authors, can help hotel managers understand the determining factors of room price, consumer choice, and behavior. Hotel managers can subsequently respond by improving room quality and hospitality service.

Using a hierarchical regression procedure, Thrane (2005) developed hedonic price models that enable the tracking of possible indirect effects of attributes on overall package tour prices through hotel star ratings. The findings allow consumers to determine the attributes for which they have to pay more, and practitioners can set strategic pricing accordingly. In another study, Thrane (2007) used log-linear regression to analyze the relationship between room rates and the existence of hotel facilities in Oslo's hotels. Findings of single rooms and double rooms revealed comparable results. Similarly, Monty and Skidmore (2003) stated the importance of evaluating willingness to pay for specific characteristics of B&B accommodations. Their findings showed that based on the data collected from Southeast Wisconsin, customers were willing to pay for hot tub, private bath, and a larger room, but not for fireplaces, themes, scenic views, and room service. Likewise, Chen and Rothschild (2013) examined the effects of different variables on hotel room rates in Taipei by employing a hedonic pricing method, which is a widely used approach for hotel room pricing. Empirical findings showed that the individual importance of most dependent variables changes, based on whether the stay is on a weekend or a weekday.

Abbruzzo, Brida, and Scuderi (2014) used graphical models to evaluate the relationships of different factors of tourist expenses. Based on the findings, accommodation expenditure was related to place of stay, accommodation type, transportation, and food & beverage expenses. In another study, Mottiar (2006) analyzed the average total expenditure of tourists based on different type of accommodations. Empirical findings showed the tourists who stayed with friends/relatives and those stayed in their own holiday homes spent the least and most amounts during their visits. Moreover, Lee and Jang (2011) applied household bid-rent function to examine the relationship of room rates in airport hotels in the US and their proximity to the city center. Findings showed room rates are simultaneously affected by the distance to the airport and the city center.

Schwartz (2000) stated that the customers who book their hotel rooms closer to the time of their stay are usually willing to pay more. According to his findings, although willingness to pay increases as time gets closer to the date of stay, the extent of the change depends on the customer's search cost. In particular, customers with a low search cost had significantly higher willingness to pay as the date of stay comes closer. Another behavioral study investigated customer willingness to pay in green hotels. Kang, Stein, Heo, and Lee (2012) found a positive relationship between the customer level of environmental concern and the willingness to pay for the green initiatives of a hotel. The findings of the study indicated the positive relationship between the hotel category and the willingness to pay, and the willingness of male customers to pay more for a premium than female customers. In their studies, both Nicolau and Más (2005) as well as Perez and Sampol (2000) found hotel accommodation is directly associated with higher tourist expenditure. As such, destination promotions should be developed with special attentions to long-haul travelers.

For the determinants of hotel room prices, Zhang, Ye, and Law (2011) used regression models to analyze whether and how hotel class, attributes of the room, and other factors influence room rates. Using data from New York, the researchers found that room quality and location are important determinants of room prices. However, the factors that can influence room rates differ greatly among the various segments of the analyzed hotels. In another study, Hung, Shang, and Wang (2010) applied quantile regression to examine the major determinants of hotel room pricing strategies. The results showed that the number of rooms, age of hotel, market condition, and number of housekeeping staff per room are the major determining attributes of hotel room rates. These results, however, did not apply to low hotel prices at the low price quantile. In addition, the proportion of foreign individual travelers positively and significantly influences room prices for high-priced quantile hotels, and allows hotel managers to setup pricing strategies accordingly.

Juaneda, Raya, and Sastre (2011) conducted a comparative study of the price components of physical characteristics and hotel and apartment locations to compare their effects on the final price of both types of accommodation. The seasonality effect of price for hotels was lower than the apartments throughout the study period. In another study, Lee (2011) used a volatility clustering modeling framework to analyze the determining factors of hotel room rates in Singapore. The findings suggested that total inbound tourists and economic performance have positive effects on hotel room rates, which indicate that the volatility of hotel room rates has a positive effect on hotel room rates.

Lastly, Schamel (2012) estimated the willingness to pay for different hotel characteristics. The major determining factors of hotel room prices include popularity ratings, hotel star ratings, weeks of advance booking, and other hotel characteristics, such as express checkout and room service. However, some factors, such as wireless Internet in the room and wellness offers, are insignificant, as consumers generally consider such as standard services.

In brief, the factors that influence hotel room rates can be summarized into four types of physical factors, which are i) room size and facilities, ii) behavioral factors, such as when to make the reservation and willingness to pay for additional service, iii) quality factors, such as star rating, and iv) other factors, such as economic performance and number of tourist arrivals.

2.2. Management's Adoption of Pricing Strategy

To provide evidence that some financial characteristics are crucial for the hotel industry to earn more profit, Hua, Nusair, and Upneja (2012) used a logit model to examine the relationship between the financial characteristics and outperformance of a hotel. Based on the findings, the authors proposed that hotel managers should use industry medians to benchmark financial performance. Similarly, Yang (2012) argued that hotel managers should integrate a demand-based pricing strategy with a supply-based strategy for product development. Arguing that hedonic pricing research has explored different variables that determine room rates (e.g., location and hotel category), Becerra, Santalo, and Silvia (2013) analyzed the effects of vertical and horizontal differentiation on pricing policies adopted by Spanish hotels. The research findings indicate that differences in hotel category explain a larger percentage of variance in both prices and discounts than hotel chains.

Consumers are often interested to find the websites that offer the lowest room rates, but they are also confused by the existence of several online distribution channels. To understand further this behavior, Law, Chan, and Goh (2007) examined online hotel room rates in Hong Kong. Among the eight selected distribution channels, websites of a local travel agent and a local reservation agent offered the lowest online room rates, while indirect distribution channels offered lower room rates than direct ones. Likewise, Herrmann and Herrmann (2014) found that hotel room rates fluctuate largely during a large event in Munich. Specifically, room rates were the highest on Friday and Saturday nights, which were followed by weekdays and Sunday. In a related study, Kim, Bojanic, and Warnick (2009) examined whether the practice of price bundling by online travel agencies (OTAs) results in actual monetary saving. Empirical findings indicated that monetary savings are manifested in the form of lower prices, and that there is an interaction effect between distribution channel and hotel class. In addition, the overall price levels were significantly higher for hotels with four and five stars because of the perceived price-quality relationship for hotel service.

To find out the relationship between price and quality in the hospitality industry, Henley, Cotter, and Herrington (2004) analyzed pricing behaviors of hotel management before and after quality change. Empirical findings showed that hotels raise prices before gaining a star and reduce prices before losing a rank. In another study, Parrilla, Font and Nadal (2007) attempted to find the relationship of hotel profit and different hotel market segments in the Balearics. Findings indicated that hotel categories, number of stars, opening behavior in a year, and locations are the critical factors. Likewise, Sainaghi (2011) claimed that hotel managers in Milan adopted pricing strategies for revenue management. The factors that these managers considered crucial are related to positioning, market orientation, and location. Similarly, Demirciftci, Cobanoglu, Beldona, and Cummings (2010) examined the actual rate parity of hotels across direct and indirect distribution channels. The findings revealed no significant differences between rates from these two types of channels. However, significant differences were found in rates within both direct and indirect channels. More importantly, the authors negated the claim of lowest rate guaranteed as stated by different hotel chains.

In summary, the abundance of prior studies on hotel room rates and the absence of a commonly agreeable method that computes the determining factors of such rates strongly hint at the need to conduct further research in the area. Hence, the present study adds values to the existing hospitality literature by examining tourist expenditures obtained from various online and offline channels on accommodation. The innovation of this study is its novelty on investigating tourist accommodation price from customers' perspective.

3. Data and Methodology

The data include a set of bookings for accommodations in Ascona-Locarno, Ticino, Switzerland, which were generated from different sales channels. In particular, the local Destination Marketing Organization (DMO) plays an important role in the promotion and sales of tourist accommodations in the area. The DMO provides two booking platforms, which comprise one online (through its own DMO website) and one offline (through its own DMO call center). The local DMO further provides accommodation owners the opportunity to use an ad hoc channel manager to manage the bookings from different channels, including OTAs and their own websites, as well as the two DMO channels. Ultimately, the channel manager registers all the successful transactions and the relevant information are saved in a database administrated by the local DMO. This set of bookings is considered in this analysis for the entire 2011.

Table 1 presents the descriptive statistics for the sample under investigation. A total of 2,728 bookings were successfully recorded for those accommodations that were bookable online and actively used the channel manager provided by the local DMO. The average total expenditure per booking is about 536 CHF (approximate exchange rate 1 CHF = 1 USD), and is characterized by a consistently high standard deviation and a large range. This result is due to the heterogeneity in both the length of stay, which varied between 1 and 14 nights for a median of 2 nights, and the travel party size, which was typically composed of 2 persons, but varied between 1 and 9 guests. In this context, the price per person per night provides a clearer pattern of the accommodation expenditure in the sample. An average of 100 CHF per person per night was spent for accommodation, which ranged from as little as 16 CHF to as much as 336 CHF. The figure for the quantiles of the price per person per night highlights a fairly symmetric distribution on the central part of the distribution, which ranged from 0.25 to 0.75 quantiles. However, the value for the 0.9 quantile suggested a long-right-tail, which is confirmed by a positive skewness value of 0.66. The non-normality of the price per person per night distribution is further proved by the Shapiro-Wilk test which the resulting statistic, equal to 0.972, implies the rejection of the null hypothesis of normality at a significance level of 0.001.

The star rating of the accommodations represented in the sample reflects the pattern commonly observed in Switzerland characterized by a consistent proportion of not-classified structures. Indeed, the star rating is assigned only to those accommodations that belong to industry association (hotelleriesussie for hotels and Swiss Tourism Federation for holiday homes). Three-star accommodations are the most popular category (45.2%), followed by four-star (23.2%) and two-star accommodations. The typology of the accommodation reflects a relevant characteristic of the subject destination, which is the considerable popularity of holiday homes. About 19% of the bookings referred to holiday homes, whereas the remaining 81% referred to hotels.

The two typologies of accommodations showed a different pattern in terms of sales channels, which was largely derived from DMO channels (81%) for holiday homes and from OTAs (58%) for hotels. The direct online channel (i.e., own website of a hotel) represented a marginal share (8.4%) for hotels and was barely present (0.6%) for the holiday homes. In general, DMO channels are well positioned for both hotels and holiday homes, and the offline call centers had a consistent share of bookings, especially for holiday homes (35.8%).

As expected, the majority of the bookings (59.0%) were made during the summer season. This result reflected the popularity of the summer activities of the destination, which is by the lake. The main purpose of visiting Ascona-Locarno is for leisure, and the bookings charged to business companies represented only a marginal share (2.5%) of the sample. The booking pattern is further characterized by a consistent heterogeneity in terms of advanced booking, with a median of 15 days prior to the time of stay and a distribution ranging from bookings made on the same day of the stay to bookings made 321 days prior to the actual stay.

TABLE 1 ABOUT HERE

To investigate the accommodation expenditure, the variable associated with the price per person per night was selected as a dependent variable. The non-price variables described in Table 1 were assumed to influence the level of expenditure, and were treated as independent variables. In particular, the following standard linear relation is formulated:

$$\ln(y_i) = \alpha + \sum_k \beta_k x_{ki} + \varepsilon_i \qquad (1)$$

where $ln(y_i)$ is the natural logarithmic transformation of the price per person per night associated with booking i, α is a constant term, β_k is the coefficient associated with the k-th independent variable x_{ki}, and ε is a Normal error. The unknown β coefficients are typically estimated by the linear least squares (or OLS) method, which estimates the conditional expectation of the dependent variable based on the set of independent variables *E(y|x)*, as follows:

$$\min \sum_i (\ln(y_i) - (\alpha + \sum_k \beta_k x_{ki}))^2 \tag{2}$$

where the parameters and variables are as defined in Equation (1). Therefore, the OLS method provides the conditional mean estimates, which are assumed to be constant along any point of the distribution of the dependent variable. In this context, Koenker and Bassett (1978) introduced the quantile regression, aiming at the estimation of conditional quantile functions, and hence allowing non-constant effects of the independent variables over the conditional distribution of the dependent variable. The underlying logic behind quantile regression is to estimate the conditional median function, which is obtained by minimizing the sum of absolute residual instead of the squared residual as performed by the OLS method (see Koenker and Hallock (2001) for a detailed discussion). Considering that the median is the 50th quantile, the estimation of different quantile functions is obtained by applying different weights to the absolute residuals. In particular, the quantile coefficients refer to the conditional quantile functions $Q_\tau(y|x)$, and are estimated as follows:

$$\min \sum_i \tau \left|(\ln(y_i) - (\alpha + \sum_k \beta_k(\tau) x_{ki})\right| + \sum_i (1-\tau)\left|(\ln(y_i) - (\alpha + \sum_k \beta_k(\tau) x_{ki})\right| \tag{3}$$

where $\tau \in (0,1)$ is the estimated conditional quantile (i.e., $\tau = 0.5$ for the median), and $\beta_k(\tau)$ is the *k-th* coefficient associated with the τ quantile and variable x_k. In common practice, the coefficients at the 10th, 25th, 50th, 75th, and 90th quantiles of the distribution of the dependent variable are estimated and reported. The semi-logarithmic specification outlined in Equation (1) made the estimated coefficients to be interpreted in terms of semi-elasticities (i.e., percentage change in the dependent variable y_i given by a unit-change in the independent variable x_{ki}).

4. Results

Table 2 shows the determinants of price per person per night, which were estimated at the 10th, 25th, 50th, 75th, and 90th quantiles. We also presented the OLS results as reference. With the exception of the variable "business" (bookings charged to business companies), all the other independent variables were significant in the OLS regression. Nevertheless, the results of the quantile estimates were mixed and less straightforward, and allowed for richer interpretations and more refined insights. Table 2 shows the estimates for each quantile, so that the effect of the set of explanatory variables is presented for each quantile, allowing the researcher to detect different impacts of a specific variable depending on the level of the dependent variable.

We divided these determinants into two groups (Table 3 shows the p-values of Wald statistics for the slope equality tests). The first group comprised determinants whose effect was constant over the conditional distribution of the dependent variable (conditional quantile estimates were not different from the conditional mean estimates obtained through OLS). The second group was composed of determinants whose impacts varied across quantiles, and were, therefore, dissimilar to the OLS estimates.

Accordingly, “business,” “summer,” “star1,” “advbook,” and “nights” showed the same effect on price per day per person in OLS and quantile estimates. Specifically, the variable “business” was not significant, which indicated that bookings charged to business companies did not lead to variation in prices, that is, they were not different from those charged to individuals. As expected, seasonality had an effect because the variable “summer” was significant. Room rates increased from the first of May through the end of September, which was consistent with the study of Juaneda, Raya, and Sastre (2011). “Star 1” (star classification was assigned only to accommodations that belonged to industry associations) had a specially strong negative effect on price compared to other higher-ranked members of the accommodation associations and in relation to establishments that were not members of any association.

The quality-price relationship seemed to exist, and, consequently, higher star rating resulted in higher room rates among hotels within the association. Although this result was foreseeable, the more interesting outcome is that hotels and holiday homes, which are not members of any association, try to position themselves higher than the two-star category, as compared to the accommodation types that belonged to associations. The number of days between the booking and the first day of the stay (Advbook) had a positive impact on price. Therefore, hotels tended to reduce their prices as the consumption day approached. The non-business character of the reservation (only 2.45% of the samples were bookings charged to business companies) might result in the need to fight perishability, and thus, price reductions are applicable. The number of nights of the stay had a negative effect on prices, which meant that longer stays were favored by accommodation firms through room rate reductions.

On the other hand, star classification (“Star 2, Star 3, Star 4, and Star 5”), distribution types (OTAs Hotel, OTAs Holiday home, DMO website Hotel, DMO website Holiday home, DMO call center Hotel, and DMO call center Holiday home), and the “number of people” presented different effects over the conditional distribution of the price.

Regarding the star classification, although the OLS estimated coefficient was significantly negative for the “Star 2” variable, the value had a positive and significant effect for the 10th and 25th quantiles, and a negative and significant effect for the 50th, 75th, and 90th quantiles. As expected, two-star establishments were less prone to set high prices, and thus, were more inclined to set low prices. A similar pattern was observed for three-star hotels.

The OLS resulted in a significant and positive (and very small) parameter with positive and significant 10th, 25th, and 50th quantile coefficients, a non-significant 75th quantile coefficient, and a significantly negative 90th quantile coefficient. As for four- and five-star establishments, positive and significant parameters were obtained from OLS estimates (these categories are associated with higher prices, as expected), and decreasing patterns were seen in the quantile estimated coefficients. These results proved that the constant effect estimated through OLS was not actually constant across the quantiles.

For the distribution used, all the indirect distribution channels (OTAs Hotel, OTAs Holiday home, DMO website Hotel, DMO website Holiday home, DMO call centre Hotel, DMO call centre Holiday home) presented negative and significant parameters compared to the direct distribution channels (own websites of the hotel and the holiday home). This result was consistent with the findings of Law, Chan, and Goh (2007). Note that the holiday home parameters were more negative than the hotel parameters, which indicated that hotels adjusted their prices closer to their intermediaries. By contrast, these intermediaries managed to reduce further the prices of holiday homes. More importantly, the intermediaries OTAs, DMO website, and DMO call center had the largest effects at the 75th quantile estimate (see Table 3). This finding implied that the difference between direct and indirect channels was biggest in high-priced establishments. On the contrary, the low-priced hotels did not show any significant difference (none of the 10th quantile parameters of hotel intermediaries were significant).

Finally, we found a significant and negative parameter for the “number of people in the group” and a significant and positive impact of the square of this variable, leading to a curvilinear effect. An increase in the number of people results in the lowering of the price per night per person, but this behavior only happens up to a point, after which, prices start augmenting.

TABLE 2 ABOUT HERE

TABLE 3 ABOUT HERE

5. Discussion and Conclusions

This paper proposed a demand-driven application of tourism expenditure for accommodation at the destination. In particular, bookings for hotels and holiday homes that were made through four different (online and offline) sales channels have been modeled through the estimation of both OLS and quantile regressions. A set of major travel characteristics (such as length of stay, travel party size, advance booking, selected sales channel, season, and purpose of travel) are assumed to be related with the expenditure for accommodation and were therefore investigated to exploit their insightful relationships. The star classification of the accommodation is further included in the model as it represents a common discriminator of price in the hotel industry.

The results confirm the statistic relevance of the variables used as explanatory factors of the accommodation expenditure. In particular, an increase of one night in the length of stay would decrease the average daily accommodation expenditure by 2.5%. Similarly, a 1% decrease in the price should, on average, be expected if the booking is made 10 days prior to the actual stay. Reflecting the seasonal nature of the destination analyzed, accommodation expenditure is expected to increase by 9.7% during the summer season (from May to September).

The estimation of a quantile regression further allowed the identification of those factors whose effects are not constant along different points in the distribution of the accommodation expenditure. Interestingly, the variables that present a differentiated effect along the expenditure distribution are star classification (except for one-star hotels), distribution channels, and travel party size.

While the daily expenditure for stays in one-star hotels is generally 30% lower than non-classified hotels, the effect associated with the other star ratings depends on the level of price. In this context, the dynamic pricing of non-classified structures compared to two- and three-star accommodations is interesting. For lower (than the median) price categories, non-classified structures are cheaper than two- and three-star structures. For higher price categories, non-classified structures are more expensive than both two- and three-star structures. This finding suggests that price, other than star rating, can indeed serve as an indicator of quality, which is well reflected on the spending behavior of tourists. Regarding the expenditure by distribution channels, the convenience of OTAs over the websites of hotels peaks in medium-high level prices. Another interesting finding is the result on travel party size which provides supporting evidence of a curvilinear effect for accommodation expenditure. This result extends to accommodation expenditure what was previously found by Aguiló and Juaneda (2000) and Thrane and Farstad (2011) for general tourism expenditure.

The findings allow the identification of several theoretical and managerial implications. This study proves the appropriateness of using a quantile regression approach in modeling tourist accommodation expenditures. Therefore, the exclusive use of OLS regression should be avoided in these types of analysis as it provides an incomplete picture of the phenomenon. Specifically, quantile regression estimates are robust to non-normal errors and to the potential existence of outliers. As the distribution of tourist expenditures is generally characterized by a long tail on account of the large values on the right tail of the distribution, the sole use of OLS could lead to spurious estimates. Also, for the specific case of the expenditure analysis, quantile regression provides a richer characterization of the data. In particular, the estimation of a quantile regression allows the identification of differentiated effects in the conditional distribution of accommodation expenditure for its explanatory variables. What is more, an analyst can detect those variables whose effect is constant over the conditional distribution of the dependent variable (in line with OLS estimates) and those dimensions whose impacts vary across quantiles (and are dissimilar to the OLS estimates). Moreover, the analysis indicates the relevance of key travel characteristics in the determination of tourist accommodation expenditure. Supporting evidence was also found in terms of the non-linear effect of travel party size, such that the variable should be treated by introducing both linear and quadratic effects.

From the managerial perspective, three major implications can be outlined from the current research. First, the results show that bookings charged to business companies are not different from those charged to individuals. Although the proportion of business reservations might be low at a particular destination, managers must remember that price sensitivity of business travelers tend to be lower, thereby not charging adequate prices for the different segments might represent an opportunity cost. This point is even more acute if accommodation establishments have the need to fight perishability, as the price paid by business travelers can compensate some empty rooms. It is important to remember that even though a hotel could be willing to sell a number of units inferior to its available units in order to maximize its profits (say, the case of a monopoly or an oligopoly), the fact that a night in a hotel cannot be stored to be sold the next night, together with the large proportion of fixed costs incurred by hotels, make them be strongly revenue-dependent. It implies that high revenue levels are normally required to survive and generate adequate profit returns. Therefore, hotels must price their rooms so that, for the scheduled time, profits are maximized, and yield management takes center stage; hence, the ability of combining room rates depending on the guest type (business travelers vs individual travelers).

Second, accommodation firms not affiliated to any association try to position themselves in the market, and it is possible to determine their position with respect to the ones included in an association. Specifically, both classified and unclassified structures need to identify the competitive positioning strategy of their rivals. Unclassified structures are more inexpensive than two- and three-star structures, but such observation only applies to lower prices and the opposite applies to higher prices. Accordingly, DMOs that are vigilant and make decisions on their destination brand can look at a competitive positioning strategy of the hotels existing at the destination, first, to ensure that the individual hotel brands comply with the expected minimum quality standards and second, to detect potential “free-riders” (i.e. hotels that achieve benefits (generally related to brand awareness, image and reputation) that they have not paid for. This way, DMOs can set some courses of action, such as rewarding the loyal contributors, establishing penalties for the free riders, or simply providing information on the situation.

Third, the results suggest that hotels adjust their prices closer to their intermediaries as these intermediaries manage to reduce the prices of holiday homes further. In an attempt to maximize the strategy of the accommodation firm, two questions emerge from the results. First, if hotels were more lenient with their intermediaries (if allowed to set lower prices), would they increase their total revenue via increments in units? Second, if holiday homes were to suggest to their intermediaries that they adjust their prices (closer to theirs), would they increase their total revenue via increases in prices? Obviously, the answers to these questions depend on the strategy and particular context of the firm, but the detection of these patterns must lead managers to consider whether the relationship with their intermediaries (e.g., in terms of price agreements) is as expected and is at the optimum. This fact also gives more importance to networking on the part of the hotels and the activities set by DMOs, as promotional activities such as fam-trips and workshops, whose main purpose is to make contacts with intermediaries, are still worthwhile.

An important avenue for further research is hereby opened. The statistical result, which shows that the constant effect estimated through OLS is not actually constant across the quantiles, can be used to determine rivalry structures. By using the “classified vs. not-classified accommodation” dichotomy, we have been able to determine the position of firms in terms of their prices. With more dimensions other than classification, such as location, specific physical attributes, or image, further studies could provide a complete structure for competition analysis and ascertain the extant strategic groups in the industry.

Finally, a limitation of the study is the fact that the data do not include certain variables that can shed some light on the tourist expenditure. Specifically, those dimensions related to socioeconomic characteristics of the individuals. While today one might find high-incomers booking on OTAs where prices can be different from a hotel’s website, inserting traditional variables such as income or occupation can lead, especially when introduced as interactions with other managerial variables, to relevant, insightful results.

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Tables

Table 1. Sample descriptive statistics

Sample = 2728 observations	**Mean (or %)**	**Median**	**St. dev.**	**Min**	**Max**
Total price (CHF)	536.73	420.00	437.12	69	5320
Length of stay (nights)	2.85	2	2.47	1	14
Price per night (CHF)	207.19	199.92	85.10	50	495
Travel party size (people)	2.14	2	0.88	1	9
Price per person per night (CHF)	103.99		42.99	16	336
		50.00	*(Quantile 0.1)*		
		73.00	*(Quantile 0.25)*		
		100.00	(Quantile 0.5 - Median)		
		130.00	*(Quantile 0.75)*		
		160.00	*(Quantile 0.9)*		
Advance booking (days)	38.38	15	51.30	0	321
Star rating (100%)					
Not-classified (n.c.)	15.03%				
1-star	2.93%				
2-star	13.42%				
3-star	45.16%				
4-star	23.20%				
5-star	0.26%				
Type of accommodation (100%)					
Hotels	80.94%				
Holiday homes	19.06%				
Hotel sale channels (100%)					
OTAs	58.29%				
Own website	8.38%				
DMO website	27.13%				
DMO call center	6.20%				
Holiday home sales channels (100%)					
OTAs	18.08%				
Own website	0.58%				
DMO website	45.58%				
DMO call center	35.77%				
Seasonality (100%)					
Summer (May - September)	59.02%				
Winter (October - April)	40.98%				
Transaction party (100%)					
Business company	2.46%				
Individual	97.54%				

Table 2. Determinants of price per person per night (OLS and quantile regression)

(Standard errors in parenthesis)

Variables	OLS	Quantiles				
		0.1	0.25	0.5	0.75	0.9
Constant	5.0410[a]	4.6119[a]	4.7935[a]	5.0010[a]	5.2487[a]	5.4623[a]
	(0.0369)	(0.0676)	(0.0451)	(0.0560)	(0.0460)	(0.0600)
BUSINESS	0.0208	-0.1660	-0.0063	0.0406	0.0476	0.0892
	(0.0322)	(0.1936)	(0.0575)	(0.0417)	(0.0369)	(0.0468)
SUMMER	0.0967[a]	0.0842[a]	0.0854[a]	0.1065[a]	0.0847[a]	0.0847[a]
	(0.0109)	(0.0181)	(0.0144)	(0.0130)	(0.0121)	(0.0132)
STAR1	-0.3034[a]	-0.3014[a]	-0.3231[a]	-0.3945[a]	-0.2903[a]	-0.3019[a]
	(0.0314)	(0.0615)	(0.0642)	(0.0665)	(0.0549)	(0.0467)
STAR2	-0.0775[a]	0.2581[a]	0.0837[a]	-0.0945[a]	-0.2212[a]	-0.3107[a]
	(0.0188)	(0.0353)	(0.0316)	(0.0333)	(0.0241)	(0.0215)
STAR3	0.0905[a]	0.3058[a]	0.1973[a]	0.0789[b]	-0.0386	-0.0504[b]
	(0.0155)	(0.0323)	(0.0310)	(0.0324)	(0.0222)	(0.0221)
STAR4	0.4606[a]	0.6786[a]	0.5560[a]	0.4369[a]	0.3286[a]	0.3079[a]
	(0.0171)	(0.0316)	(0.0332)	(0.0348)	(0.0234)	(0.0235)
STAR5	0.7437[a]	1.1517[a]	0.8398[a]	0.6811[a]	0.6512[a]	0.4616[a]
	(0.0964)	(0.0623)	(0.0620)	(0.0926)	(0.0645)	(0.0378)
ADVBOOK	0.0012[a]	0.0009[a]	0.0011[a]	0.0014[a]	0.0012[a]	0.0011[a]
	(0.0001)	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
OTAs Hotel	-0.1148[a]	-0.0256	-0.1025[a]	-0.1063[a]	-0.1823[a]	-0.1236[a]
	(0.0200)	(0.0323)	(0.0254)	(0.0287)	(0.0192)	(0.0252)
OTAs Holiday home	-0.5191[a]	-0.5440[a]	-0.5973[a]	-0.5562[a]	-0.6636[a]	-0.4709[a]
	(0.0359)	(0.1059)	(0.0618)	(0.0488)	(0.0525)	(0.0812)
DMO website Hotel	-0.0705[a]	-0.0522	-0.0587[b]	-0.0578	-0.1365[a]	-0.1111[a]
	(0.0218)	(0.0459)	(0.0292)	(0.0297)	(0.0212)	(0.0222)
DMO website	-0.4848[a]	-0.5555[a]	-0.5689[a]	-0.5157[a]	-0.5883[a]	-0.5325[a]
Holiday home	(0.0284)	(0.0629)	(0.0505)	(0.0395)	(0.0355)	(0.0414)
DMO call centre	-0.0613[b]	0.0050	0.0026	-0.0728[b]	-0.1602[a]	-0.0673
Hotel	(0.0293)	(0.0777)	(0.0373)	(0.0348)	(0.0276)	(0.0410)
DMO call centre	-0.4326[a]	-0.4629[a]	-0.4628[a]	-0.4866[a]	-0.6018[a]	-0.4917[a]
Holiday home	(0.0310)	(0.0523)	(0.0501)	(0.0489)	(0.0386)	(0.0453)
NIGHTS	-0.0254[a]	-0.0172[b]	-0.0178[a]	-0.0253[a]	-0.0214[a]	-0.0131[b]
	(0.0030)	(0.0067)	(0.0048)	(0.0040)	(0.0033)	(0.0059)
Number of people	-0.2602[a]	-0.3629[a]	-0.2715[a]	-0.2215[a]	-0.1758[a]	-0.2811[a]
	(0.0171)	(0.0269)	(0.0158)	(0.0168)	(0.0209)	(0.0329)
Number of people^2	0.0131[a]	0.0264[a]	0.0150[a]	0.0097[a]	0.0050[b]	0.0197[a]
	(0.0023)	(0.0027)	(0.0019)	(0.0019)	(0.0020)	(0.0048)

Notes:[a] prob < 1%; [b] prob < 5%

Table 3. Significant differences among quantiles (p-values)

	0.1, 0.25	0.25, 0.5	0.5, 0.75	0.75, 0.9
BUSINESS	0.3453	0.3319	0.8527	0.3169
SUMMER	0.9416	0.1096	0.0703	0.9981
STAR1	0.7144	0.3294	0.1008	0.9392
STAR2	0.0000	0.0000	0.0000	0.0000
STAR3	0.0010	0.0001	0.0000	0.5809
STAR4	0.0003	0.0003	0.0002	0.3581
STAR5	0.0000	0.0406	0.7101	0.0005
ADVBOOK	0.2126	0.0661	0.1317	0.3809
SALE1H	0.0061	0.8820	0.0020	0.0083
SALE1V	0.5484	0.4542	0.0273	0.0041
SALE3H	0.8687	0.9730	0.0020	0.2271
SALE3V	0.8110	0.2302	0.0492	0.1315
SALE4H	0.9711	0.0287	0.0054	0.0075
SALE4V	0.9985	0.6117	0.0080	0.0073
NIGHTS	0.9195	0.0783	0.2670	0.0974
PAX	0.0001	0.0012	0.0139	0.0004
PAX^2	0.0000	0.0036	0.0145	0.0006